TITLE: Predicting physical activity energy expenditure in wheelchair users with a multi-sensor device

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ABSTRACT

Aim To assess the error in predicting physical activity energy expenditure (PAEE), using a multi-sensor device, in wheelchair users and to examine the efficacy of using an individual heart rate calibration method. **Methods** Fifteen manual wheelchair users (36 ± 10 years, 72 ± 11 kg) completed ten activities: resting, folding clothes, wheelchair propulsion on a 1% gradient (3,4,5,6 and 7 km·hr^{-1}) and propulsion at 4 km·hr^{-1} (with an additional 8% of body mass, 2% and 3% gradient) on a motorised wheelchair treadmill. Criterion PAEE was measured using a computerised indirect calorimetry system. Participants wore a combined accelerometer and heart rate monitor (Actiheart^{TM}). Participants also performed an incremental arm crank ergometry test to exhaustion which permitted retrospective individual calibration of the Actiheart^{TM} for the activity protocol. Linear regression analysis was conducted between criterion (indirect calorimetry) and estimated PAEE from the Actiheart^{TM} using manufacturer's proprietary algorithms (group calibration; GC) or individual heart rate calibration (IC). Bland-Altman plots were used and mean absolute error calculated to assess the agreement between criterion values and estimated PAEE. **Results** Predicted PAEE was significantly ($p<0.01$) correlated with criterion PAEE (GC; r=0.76 and IC; r=0.95). The absolute bias ± 95% limits of agreement were 0.51 ± 3.75 kcal·min^{-1} and -0.22 ± 0.96 kcal·min^{-1} for GC and IC, respectively. Mean absolute errors across the activity protocol were 51.4 ± 38.9% using GC and 16.8 ± 15.8% using IC. **Summary** PAEE can be accurately and precisely estimated using a combined accelerometer and heart rate monitor device, with integration of an individual heart rate calibration. Inter-individual variance in cardiovascular function and response to exercise is high in this population. Therefore, in manual wheelchair users, we advocate the use of an individual heart rate calibration when using the Actiheart^{TM} to predict PAEE.

BACKGROUND

There is a paucity of research focussing on the impact of physical activity on the health of disabled groups, particularly wheelchair users. There are an estimated 750,000 wheelchair users in the United Kingdom. Locomotion and movement patterns in wheelchair users are very different to ambulatory individuals and, as such, further studies are required to develop tools to quantify physical activity levels.

Recently, through technological advancements, there has been an increase in the application of accelerometer-based monitors to measure free-living physical activity energy expenditure (PAEE).[1] However, the assessment of physical activity in wheelchair users is still reliant on subjective self-report methods.[2, 3] The Physical Activity Recall Assessment for People with Spinal Cord Injury (PARA-SCI) has relatively modest associations (R^2 = 0.62) with criterion measures of PAEE [4] and limited utility due to exclusion of subjective appraisals and the technical complexity of administration.[5] Criterion or 'gold standard' measures (i.e. indirect calorimetry, observation and doubly-labelled water) are highly accurate and often compared to outputs from activity monitors during laboratory validation trials. Yet these measures require expensive/sophisticated equipment or are impractical for use outside of the laboratory. Pedisic & Bauman [6] suggested that accelerometer-assessed PAEE using algorithms intrinsic to certain devices may not be generalizable to a target population, certainly an issue for groups with differing movement patterns such as wheelchair users. Therefore, the logical first step prior to using objective devices in surveillance research, is to ensure that these have been validated for use in specific populations.

Previous research has assessed the validity of a number of objective methods to predict physical activity levels of wheelchair users. These include attaching a custom data logger onto the wheel [7] or a tri-axial accelerometer [8] to the frame of the wheelchair to capture certain mobility characteristics such as average speed and distance travelled. Whilst unobtrusive, these devices offer limited information on the intensity of activities performed and offer somewhat modest associations with energy expenditure. Recently, hand rim propulsion power [9] was evaluated to address this limitation. However, any device on the wheelchair cannot distinguish between self or assisted propulsion and cannot quantify non-wheelchair activity. An alternative approach has been the use of body-borne movement sensors. Previous research has identified that the wrist is the most appropriate anatomical location to accurately predict physical activity in wheelchair users across a range of propulsion speeds [10] and in a laboratory environment.[11] Whilst this is encouraging, accelerometry alone does not capture the physiological strain associated with movement behaviours that produce similar acceleration profiles but have a different energy cost, such as changing gradient or load carriage.[12]

Multi-sensor devices, which integrate accelerometry and physiological signals to predict PAEE, are commonly used in studies of able-bodied participants. Previous validation work in wheelchair users has focussed on the integration of dual-axis accelerometry and physiological measures (e.g. heat flux) to predict energy expenditure (EE).[13, 14] Previous studies in able-bodied participants have supported the utility of combined heart rate (HR) and accelerometer devices to estimate EE.[15, 16] The Actiheart (AHR) is a commercially available multi-sensor device which incorporates HR monitoring and accelerometry into a single unit. It is widely used to measure free-living PA in able-bodied individuals [17, 18] and further research, in diverse populations, has been recommended.[19] The aim of this study was to assess the error of the AHR device in predicting PAEE in wheelchair users and to assess the efficacy of individual HR calibration.

METHODS

Participants

Fifteen male manual wheelchair users (n = 15) volunteered to participate in this study, which was approved by the University of Bath's Research Ethics Approval Committee for Health (REACH). Each participant was informed of any potential risks and benefits and signed an informed consent form prior to taking part in the study. Time since injury (TSI) was self-reported based on when the medical condition was first diagnosed by a clinician. All participants provided written, informed consent. Demographic characteristics of the participants are presented in Table 1. A 20 ml fasted blood sample was obtained from the antecubital vein to be analysed for cardiovascular disease risk biomarkers. These data are outside the scope of this manuscript and have not been presented herein.

Study protocol

Prior to testing, participants were asked to refrain from caffeinated drinks and vigorous exercise for at least 10 h and 24 h, respectively. The mass of the wheelchair and participant was recorded in light clothing to the nearest 10 g using platform wheelchair scales (Detecto ® BRW1000, Missouri, USA). The wheelchair, along with participant's shoes were weighed separately and subtracted from the total mass.[20] Supine length was also measured using a metallic tape (Lufkin, US).

Participants completed a wheelchair propulsion protocol on an adapted treadmill (HP Cosmos Saturn 250/100r, HaB International Ltd, UK), across a range of treadmill velocities (3-7 km·hr^{-1}) and gradients (1-3%), including load-carriage (+8% body mass) and a folding clothes task. The full activity protocol is described in detail elsewhere.[21] Each activity (table 2) was assigned in order of intensity and lasted for six minutes interspersed with four minute recovery periods.

Assessment of energy expenditure

Expired gases were analysed continuously during each activity (TrueOne® 2400, ParvoMedics, UT) using a previously validated system.[22] Oxygen uptake ($\dot{V}O_2$) and carbon dioxide production ($\dot{V}CO_2$) were used to estimate EE (kcal·min^{-1}) in each activity. A Polar ® Team HR monitor (Polar Electro Inc., NY, USA) was also worn to simultaneously monitor HR.

Participants wore an AHR (ActiheartTM, Cambridge Neurotechnology Ltd, Papworth, UK), which integrates accelerometer and HR signals. The AHR unit has been described previously.[15] The unit was fitted using two adhesive ECG chest electrodes, according to manufacturer's instructions. AHR's were initialised to long-term recording with 30 s epochs. PAEE was calculated using the Branched Model technique.[23]

Resting Measures

Following a 10-min rest in a semi-recumbent position, HR and resting metabolic rate (RMR) were measured.[24] Breath-by-breath data were averaged into four 5-min samples, with additional samples collected if values varied by >100 kcal·day^{-1}. The mean of these samples was accepted as RMR.

Incremental arm crank ergometry test

Participants underwent a 9-12 minute peak oxygen uptake ($\dot{V}O_2$ peak) test using an electrically braked arm crank ergometer (Lode Angio, Groningen, Netherlands). This was conducted at the end of the activity protocol, using a continuous, incremental test until volitional exhaustion. A cadence of 75 rpm was required throughout and a starting intensity of 35 W was typically chosen, although this was based on participants training history. The resistance was increased by 14 W every three minutes. EE and HR were averaged over the final min of each stage.

Twenty-four-hour record

Participants were asked to carry out their normal daily activities for 24 h while being monitored using AHR to determine sleeping HR.[15] This provided a 24 h 'snapshot' of habitual physical activity. Furthermore, permanent wheelchair users (n = 13) were asked to log their physical activity as accurately as possible to estimate PAEE using the adapted physical activity compendium.[25] Twenty-four-hour PAEE was estimated from self-reported PA and AHR. These data are only available for 8 participants.

Data handling

Assuming that dietary-induced thermogenesis was negligible (i.e. participants were fasted), RMR ($kcal \cdot min^{-1}$) was subtracted from total energy expenditure, to generate PAEE for each activity. Comparisons between the 'criterion' measurement of PAEE (indirect calorimetry) and AHR were made between the final 2-min of each activity.

Common equations to predict RMR in the general population are inappropriate to use for individuals with an SCI.[26] Measured RMR was entered, as the Schofield equation over-predicted by 12% (range -6 to 27%). Sleeping HR, measured during the 24 hr record, and max HR measured during the $\dot{V}O_2$ peak test, were also entered into the AHR software.

Measured EE values from the rest test and during $\dot{V}O_2$ peak assessment were entered into the 'other HR calibration' tab in the AHR software as per manufacturer's instructions to derive an individual HR calibration (IC) model.

Pearson product moment correlation coefficients (r) and coefficients of determination (R^2) statistics were conducted to assess the association between criterion PAEE and predicted PAEE (generic group calibration; GC and IC). Standard Error of the Estimate (SEE) was calculated for each correlation. Error statistics, including mean absolute error (MAE) and mean signed error (MSE) were calculated. As absolute error is likely to increase with exercise intensity,[27] percentage error of estimate was also calculated. R^2, r and SEE statistics were determined to assess the relationship between twenty-four-hour self-reported PAEE and predicted PAEE (GC and IC). Independent t-tests were performed to assess differences between predicted PAEE (GC and IC) and the physical activity log during the twenty-four-hour follow-up. Statistical significance was set at *a priori* of $\alpha < 0.05$.

RESULTS

Accelerometer counts, HR and RPE all increased linearly with increasing exercise intensity (Table 2). Absolute HR on its own explained 57% of the overall variance in PAEE ($r = 0.76$, SEE = 1.07 $kcal\cdot min^{-1}$). Acceleration along the longitudinal axis of the trunk explained 65% of the variance in the prediction of PAEE ($r = 0.81$, SEE = 0.96 $kcal\cdot min^{-1}$). Three and two participants were unable to complete the 7$km\cdot hr^{-1}$ propulsion speed and 4$km\cdot hr^{-1}$ (3% gradient) tasks, respectively. Unusable HR traces were recorded for one participant in the folding clothes and 4$km\cdot hr^{-1}$ (3% gradient) trials, and for separate participants in the 3 and 5 $km\cdot hr^{-1}$ propulsion trials. These data points were therefore excluded from the analyses.

Table 1 Participant characteristics

Variable	Mean ± SD	Range (lowest – highest)
Age (years)	36 ± 11	19 - 50
Body mass (kg)	72.7 ± 10.2	54.2 - 87.5
Height (m)	1.70 ± 0.13	1.40 - 1.88
Time since injury (years)	16 ± 15	2 - 50
Sleep HR ($b \cdot min^{-1}$)	56 ± 11	42 – 74
Rest HR ($b \cdot min^{-1}$)	65 ± 12	50 – 88
RMR ($kcal \cdot day^{-1}$)	1621 ± 248	1201 – 2152
$\dot{V}O_2$ peak ($ml \cdot kg^{-1} \cdot min^{-1}$)	28.3 ± 6.9	16.7 – 41.1
Reason for WC use	SCI[1] (T1 – L4) (n = 8), Spina bifida (n = 3), Scoliosis (n = 1), Cerebral Palsy (n = 1), Amputation[2] (n = 1), AB[3] (n = 1)	

[1] All SCI volunteers indicated that they had complete lesions.
[2] Regular wheelchair user (>70% of locomotion)
[3] AB wheelchair basketball player (> two years)
AB: Able-bodied, SCI: Spinal Cord injury, WC: Wheelchair

Table 2 Measured PAEE, Predicted GC and IC PAEE, heart rate, accelerometer counts, RPE and number of participants per trial for each activity (mean ± SD)

Activity	Measured PAEE ($kcal \cdot min^{-1}$)	Predicted PAEE ($kcal \cdot min^{-1}$)		Heart rate ($b \cdot min^{-1}$)	Acceleration ($counts \cdot min^{-1}$)	RPE	n
		GC	IC				
Resting	0.0 ± 0.0	0.1 ± 0.2	0.1 ± 0.1	65 ± 12	0 ± 0	-	15
Folding clothes	1.1 ± 0.2	0.8 ± 0.6	0.6 ± 0.2	85 ± 15	6 ± 5	8 ± 2	14
$3km \cdot hr^{-1}$	1.9 ± 0.4	1.8 ± 1.0	1.7 ± 0.6	90 ± 13	70 ± 50	9 ± 2	14
$4km \cdot hr^{-1}$	2.4 ± 0.6	2.7 ± 1.7	2.3 ± 0.7	97 ± 20	127 ± 100	10 ± 3	15
$5km \cdot hr^{-1}$	3.2 ± 1.0	4.0 ± 2.9	3.0 ± 1.1	114 ± 23	160 ± 95	11 ± 3	14
$6km \cdot hr^{-1}$	4.3 ± 1.7	5.5 ± 3.7	3.9 ± 1.6	130 ± 33	229 ± 116	13 ± 3	15
$7km \cdot hr^{-1}$	4.7 ± 0.9	5.4 ± 2.7	4.1 ± 1.0	136 ± 26	282 ± 137	14 ± 3	12
$4km \cdot hr^{-1}$ (+ 8% of body mass)	2.6 ± 0.7	3.4 ± 2.3	2.6 ± 0.8	111 ± 20	112 ± 80	10 ± 3	15
$4km \cdot hr^{-1}$ (2% gradient)	3.2 ± 0.9	4.2 ± 2.8	3.2 ± 1.2	119 ± 24	156 ± 110	12 ± 3	15
$4km \cdot hr^{-1}$ (3% gradient)	4.0 ± 1.0	4.6 ± 2.3	3.5 ± 0.9	128 ± 22	162 ± 86	13 ± 4	12

Criterion PAEE was very strongly and near perfectly associated with GC ($r = 0.76$, $P < 0.01$) and IC ($r = 0.95$, $P < 0.01$), respectively. The GC explained 57% of variance in the prediction of PAEE with a SEE of 1.07 $kcal \cdot min^{-1}$, compared to the IC which explained 91% of variance in PAEE with a SEE of 0.49 $kcal \cdot min^{-1}$ (Figure 1).

[INSERT FIGURE 1 ABOUT HERE]

The degree of agreement between estimated and criterion PAEE is displayed in Figure 2 a-b. The mean bias ± 95% Limits of Agreement (LoA) was 0.51 ± 3.75 $kcal \cdot min^{-1}$ and -0.22 ±

0.96 kcal·min^{-1} for the GC and IC, respectively. Error statistics between the criterion and estimated PAEE for each activity are shown in table 3. Removal of these data for the able-bodied basketball player did not impact the nature of the regression relationships or error statistics in any meaningful way.

[INSERT FIGURE 2 ABOUT HERE]

Table 3 Mean Signed Error (MSE) and Mean Absolute Error (MAE) expressed as kcal·min^{-1} and a percentage of predicted PAEE for the GC and IC.

Activity	MSE (kcal·min^{-1})		Mean percentage error (%)		MAE (kcal·min^{-1})		Mean absolute percentage error (%	
	GC	IC	GC	IC	GC	IC	GC	IC
Resting	0.08 ± 0.18	0.05 ± 0.10	-	-	0.08 ± 0.18	0.05 ± 0.10	-	-
Folding clothes	-0.30 ± 0.75	-0.46 ± 0.17	-19.1 ± 78.9	-43.1 ± 16.2	0.68 ± 0.39	0.46 ± 0.17	66.3 ± 43.5	43.1 ± 1
3km·hr^{-1}	-0.08 ± 0.98	-0.16 ± 0.41	-4.3 ± 52.6	-8.5 ± 21.5	0.80 ± 0.52	0.30 ± 0.31	43.1 ± 28.0	16.2 ± 1
4km·hr^{-1}	0.34 ± 1.43	-0.10 ± 0.49	12.9 ± 53.8	- 3.8 ± 20.7	1.07 ± 0.97	0.32 ± 0.37	42.4 ± 33.9	13.4 ± 1
5km·hr^{-1}	0.83 ± 2.37	-0.14 ± 0.41	24.1 ± 65.6	-4.4 ± 12.7	1.83 ± 1.66	0.34 ± 0.25	56.5 ± 38.6	10.4 ±
6km·hr^{-1}	1.18 ± 2.65	-0.43 ± 0.45	26.8 ± 62.0	-9.5 ± 12.0	2.23 ± 1.79	0.50 ± 0.37	54.7 ± 37.5	12.0 ±
7km·hr^{-1}	0.77 ± 2.68	-0.55 ± 0.71	19.1 ± 59.3	-11.0 ± 15.3	2.15 ± 1.68	0.68 ± 0.57	48.6 ± 36.6	14.2 ± 1
4km·hr^{-1} (+ 8% of body mass)	0.80 ± 1.89	0.04 ± 0.52	28.4 ± 63.4	3.1 ± 21.6	1.50 ± 1.36	0.37 ± 0.36	56.8 ± 37.7	15.6 ± 1
4km·hr^{-1} (2% gradient)	0.93 ± 2.27	-0.08 ± 0.52	23.3 ± 60.1	-4.1 ± 16.3	1.62 ± 1.81	0.40 ± 0.32	47.5 ± 42.2	12.5 ± 1
4km·hr^{-1} (3% gradient)	0.58 ± 2.34	-0.50 ± 0.51	19.7 ± 72.6	11.9 ± 12.7	1.74 ± 1.60	0.56 ± 0.44	50.4 ± 54.1	13.6 ± 1
All Activities	**0.51 ± 1.90**	**-0.22 ± 0.49**	**14.6 ± 63.2**	**-10.1 ± 20.7**	**1.35 ± 1.44**	**0.39 ± 0.37**	**51.4 ± 38.9**	**16.8 ± 1**

Twenty-four-hour record

The mean ± SD reference method-derived PAEE (self-reported PA log) was 662 ± 353 kcal·day^{-1}, but predicted to be 631 ± 428 kcal·day^{-1} by GC, and 588 ± 500 kcal·day^{-1} by IC. There were no significant difference in predicted PAEE between the reference standard and both AHR methods. PAEE, quantified by the reference method, was very strongly associated with IC (R^2 = 0.50, P = 0.03) but only moderately associated with GC (R^2 = 0.16, P = 0.24) (Figure 3). The SEE were 269 and 365 kcal·day^{-1} for the IC and GC, respectively.

[INSERT FIGURE 3 ABOUT HERE]

DISCUSSION

This study aimed to assess the validity of using a multi-sensor (AHR) device to predict PAEE in a heterogeneous sample of wheelchair users. These results show that, accounting for inter-individual variance by conducting individual HR calibration, can improve the accuracy of predicting PAEE. IC better estimated PAEE than GC and explained an additional 34 percent of the variance in PAEE (91% vs 57%), when measured across a range of activities conducted in a controlled laboratory environment. Furthermore, habitual 24-hour free living PAEE was significantly correlated (R^2 = 0.50, P = 0.03) with the reference standard physical activity log in a subsample of permanent wheelchair users. These findings highlight the importance of using individual heart rate calibration when practitioners and researchers use multi-sensor devices, incorporating HR, to predict PAEE in wheelchair users.

Laboratory protocol: sources of error with using solely accelerometry or heart rate

Tri-axial accelerometers worn on the wrist have been found to predict 86 and 74% of the variance in predicting PAEE and $\dot{V}O_2$, respectively, in wheelchair users across a range of propulsion speeds [10] and in a laboratory environment.[11] However, these previous studies did not include gradients or additional mass on the chair. Previous work using an identical activity protocol to ours found that raw acceleration outputs from a GENEActiv device worn on the wrist explained 77% of the variance in predicting PAEE.[21] However the GENEActiv under-predicted PAEE by 10.6 and 20.3% during the 2 and 3% gradients, respectively. Mean absolute error was also 22.6% for the eight percent of body mass task.[21] In the present study, IC under-predicted by 4.1% and over predicted by 11.9% during the 2 and 3% gradients, respectively. Furthermore, MAE was not noticeably elevated for the gradient and load carriage tasks compared to $4 km \cdot hr^{-1}$ trial. This emphasises how integrating individually calibrated HR and acceleration data better captures the differing energy cost of activities despite similar acceleration profiles.

Heart rate has benefits as a physiological variable as it increases linearly and proportionately with exercise intensity and thus oxygen uptake.[28] Heart rate alone in this study explains 57% of the variance in the prediction of PAEE. Hayes *et al,* [29] found that HR alone only explained 8.5% of the variance in measured EE in individuals with a SCI, but this improved to 55% when an IC was performed. Simply using raw HR data may not be useful to predict PAEE due to a large degree of inter-individual variance in the HR-PAEE relationship.[30] Some of the inter-individual variance can be accounted for by using HR above resting level and adjusting for sex.[15,23] These variables are factored into the AHR proprietary algorithms (GC), which might help capture generic differences in cardiovascular function.

As HR at lower exercise intensities is affected by other factors, such as psychological or thermal stress, integration of acceleration values may offer a more reliable prediction of PAEE. This is an issue when monitoring a population who predominantly perform sedentary and light intensity activities in a free-living environment.[31] To counteract this issue with HR, during low intensity activities the branched model equation,[23] intrinsic to the AHR software, gives a relatively low weighting to HR in the prediction of PAEE. For higher intensity activities, where HR has been shown to be more accurate in predicting PAEE for individuals with a SCI,[29] the AHR utilises the branch which favours HR over acceleration in the prediction of PAEE. Even with these processing features our results suggest that combining HR and acceleration along the longitudinal axis of the trunk explains no more of the variance in the prediction of PAEE than HR alone (57%), when using GC.

Laboratory protocol: Comparison of GC and IC

The movement patterns of wheelchair users are primarily restricted to the upper limbs, as such exercise appears to elicit a somewhat different $\dot{V}O_2$-HR relationship. Raymond *et al.,* [32] showed that $\dot{V}O_2$ was 25 % higher (1.58 L·min^{-1} vs. 1.26 L·min^{-1}), but HR was 13 % lower (132 b·min^{-1} vs. 149 b·min^{-1}) during combined arm & electrical stimulation-induced leg cycling exercise compared to arm cranking exercise alone at the same power output in individuals with a SCI. The lack of lower limb muscle innervation and absence of the skeletal muscle pump leads to a reduction in venous return and a compensatory increase in HR to maintain cardiac output. As such, the gradient of the $\dot{V}O_2$-HR relationship for upper body exercise may be shallower than for lower body exercise. The GC model derived from Brage *et al.,* [30] and utilised here was designed to predict energy expenditure during ambulation. The 14.6% mean PAEE over-prediction across all activities for the GC could be a result of HR being misinterpreted as corresponding to a higher $\dot{V}O_2$.

Visual inspection of Figure 2a indicates a considerable degree of heteroscedasticity, and the sizeable 95% LoA (± 3.75 kcal·min^{-1}) shows a large degree of inter-individual variance for the GC, potentially linked to disability aetiology. For individuals with higher level SCI (≥ T6: n = 8) normal cardiovascular homeostasis can be disrupted.[33] Autonomic nervous system disruption can result in a blunted CV response to exercise and, in some instances, an absence of sympathetic drive to increase HR above 130 b·min^{-1}.[34] Our results reflect the variability in HR responses to exercise in this population, with peak HR responses ranging from 130 to 200 b·min^{-1}. Another factor known to have an impact on the HR-PAEE relationship is the variance in fitness.[35] Our sample had a wide spread of aerobic capacities, with peak oxygen uptake ranging from 16.7 to 41.1 $ml \cdot kg^{-1} \cdot min^{-1}$. The range in aerobic capacity in wheelchair users is large and reflects the degree of functional impairment and autonomic nervous system disruption in certain conditions.[36] Considering the type of exercise performed, the attenuated CV responses to exercise and large variation in fitness, an individual HR calibration is therefore of upmost importance when assessing PAEE in wheelchair users.

Initial research into the validity of using another multi-sensor activity monitor (SWA) in wheelchair users revealed sizeable EE estimation errors ranging from 24.4 to 125.8% during activities from resting and deskwork to wheelchair propulsion and arm crank ergometry.[13] This error was likely a result of the manufacturer's prediction model not being able to classify the types of upper body physical movements commonly performed by wheelchair users. More recent work,[14] using new prediction models to track these upper body movements, has reported reduced mean absolute estimation errors of 16.8%. This is identical to that reported for IC in this present study.

Twenty-four hour comparison

The majority of physical activity validation research in this population has mostly been performed in a controlled-laboratory environment. In this study, free-living 24 hr PAEE was compared to a self-reported physical activity log to confer concurrent validity. This reference method has been used previously in wheelchair users.[37] Our analysis was conducted using a relatively small subsample of participants, as physical activity logs from five of the full-time wheelchair users lacked detailed information to derive an accurate estimation of PAEE. Considering the difficulties with criterion PAEE monitoring during free-living for individuals who use a wheelchair, other researchers have encouraged simply evaluating the agreement and disagreement between measures.[38] In this study, IC 24-hr free-living predicted PAEE was significantly associated with the reference method ($r = 0.72$) whereas GC was not ($r = 0.41$).

Strengths and limitations

A significant strength of the current study was that we used a comprehensive wheelchair propulsion protocol consisting of various velocities and gradients, as well as an activity of daily living. Also, individual differences in RMR were accounted for, which previous studies have not. A potential limitation was that only one activity of daily living was included. However, this allowed us identify the relatively large error estimate, even with the IC (error 43.1%). This reflects the somewhat atypical movement patterns associated with such tasks. More activities of daily living and those of moderate-vigorous intensity should be included in future studies. There was a diverse range of disabilities within our participant sample, yet this is in keeping with previous research [9] and in accordance with best practice recommendations for physical activity validation studies.[39] Many previous studies have focussed solely on individuals with a SCI [4, 14] but, compared to the present study, these previous results are limited in their generalisability to other individuals who use wheelchairs.

In conclusion, we demonstrated that PAEE can be accurately predicted using a multi-sensor device, which incorporates acceleration and heart rate, in wheelchair users. The error associated with predicting PAEE in manual wheelchair users, is improved approximately threefold by using individual heart rate calibration. Considering the inter-individual variance in cardiovascular response to exercise is high among individuals who use wheelchairs, we advocate the importance of using an individual HR calibration.

What are the new findings?

- Physical activity energy expenditure during wheelchair propulsion can be accurately predicted using a multi-sensor device (Actiheart^{TM}), which incorporates measures of acceleration and individually calibrated HR.
- Encouragingly, the inclusion of a physiological signal (e.g. HR) can capture the physiological strain associated with behaviours that produce similar acceleration profiles but have a different energy cost, such as changing gradient or load carriage.
- This method may be used as an alternative for assessing PAEE in a habitual free-living environment for individuals who use wheelchairs.

How might the study impact clinical practice?

- Clinicians may use this PAEE assessment method to assess the efficacy of health behaviour change interventions in this at risk population. The accurate feedback might encourage an increase in physical activity levels for individuals who use a wheelchair.
- Eventually, this methodology may give clinicians and researchers a better indication of the volume and intensity of physical activity necessary to achieve optimal health in individuals who use wheelchairs.

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Contributors TEN, JPW, DT and JB conceptualised this paper and developed the study protocol. TEN and JPW collected and analysed the data. All authors were involved in interpretation and review of the results. TEN drafted the manuscript and revised it according to feedback from the other authors. All authors have reviewed and approved the final version of the manuscript.

Competing interests None.

Patient consent Obtained.

Ethics approval University of Bath Research Ethics Approval Committee for Health (REACH).

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FIGURE LEGENDS

Figure 1 Scatterplots showing the relationship between criterion PAEE and predicted PAEE using GC (a) and IC (b). *The straight line represents the best fit, and the dashed line indicates the line of identity.*

Figure 2 Bland and Altman plots for the criterion and estimated PAEE, using GC (a) and IC (b). *Bold line represents the mean difference and dashed lines represent the upper and lower 95% LoA.*

Figure 3 The relationship between predicted PAEE GC (○ dash/ dot line) and IC (▲ solid line) against the reference physical activity log method.

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